Temporal and spatial variations of net primary productivity and its response to groundwater of a typical oasis in the Tarim Basin, China

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Abstract: Net primary productivity (NPP) of the vegetation in an oasis can reflect the productivity capacity of a plant community under natural environmental conditions. Owing to the extreme arid climate conditions and scarce precipitation in the arid oasis regions, groundwater plays a key role in restricting the development of the vegetation. The Qira Oasis is located on the southern margin of the Taklimakan Desert (Tarim Basin, China) that is one of the most vulnerable regions regarding vegetation growth and water scarcity in the world. Based on remote sensing images of the Qira Oasis and daily meteorological data measured by the ground stations during the period 2006–2019, this study analyzed the temporal and spatial patterns of NPP in the oasis as well as its relation with the variation of groundwater depth using a modified Carnegie Ames Stanford Approach (CASA) model. At the spatial scale, NPP of the vegetation decreased from the interior of the Qira Oasis to the margin; at the temporal scale, NPP of the vegetation in the oasis fluctuated significantly (ranging from 29.80 to 50.07 g C/(m^2•month)) but generally showed an increasing trend, with the average increase rate of 0.07 g C/(m^2•month). The regions with decreasing NPP occupied 64% of the total area of the oasis. During the study period, NPP of both farmland and grassland showed an increasing trend, while that of forest showed a decreasing trend. The depth of groundwater was deep in the south of the oasis and shallow in the north, showing a gradual increasing trend from south to north. Groundwater, as one of the key factors in the surface change and evolution of the arid oasis, determines the succession direction of the vegetation in the Qira Oasis. With the increase of groundwater depth, grassland coverage and vegetation NPP decreased. During the period 2008–2015, with the recovery of groundwater level, NPP values of all types of vegetation with different coverages increased. This study will provide a scientific basis for the rational utilization and sustainable management of groundwater resources in the oasis.

Keywords: net primary productivity; Carnegie Ames Stanford Approach; groundwater depth; land use; NDVI; Qira Oasis

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1 Introduction

Net primary productivity (NPP) is an important component of the terrestrial carbon cycle and a significant indicator reflecting the changes of global climatic conditions (Gao et al., 2013; Yang et al., 2016; Xu et al., 2020). Analyzing and discussing the temporal and spatial variation patterns of NPP in the regional vegetation ecosystem not only is of great significance to understand the response of the ecosystem to climate change, but also provides a scientific basis for eco-environmental protection, plant productivity estimation, effective natural resources management, and determination of corresponding social and economic development strategies.

In recent years, there are plenty of models with which to estimate NPP, which can be summarized in three categories (Ruimy et al., 1994): statistic models, process models, and parametric models. Statistic models are those related to climate, which estimate NPP based on climatic factors. In process models, more parameters such as temperature and moisture are introduced based on parametric models. Parametric models are expressed by two factors, i.e., the photosynthetically active radiation absorbed by vegetation and the solar energy conversion efficiency. Currently, the Carnegie Ames Stanford Approach (CASA) is a solar energy utilization efficiency model that is widely applied for the estimation of regional NPP (Hadian et al., 2019). The CASA model, developed by Potter et al. (1993), is a global estimation model of NPP of the terrestrial vegetation based on Monteith's method of calculating plant productivity. The advantages of the model are summarized as follows: (1) the model is relatively simple, requiring few parameters; (2) the vegetation and photosynthetically active radiation information can be obtained from remote sensing data so that vegetation coverage can be classified; and (3) the dynamic temporal and spatial monitoring of NPP can be realized based on multitemporal remote sensing data (Field et al., 1995; Chen et al., 2003; Li et al., 2018; Guo et al., 2020).

Due to its simplicity and accuracy, the CASA model has become a mature approach widely used in the estimation of NPP (Mao et al., 2014). For example, Ren et al. (2020) explored the variation characteristics of NPP through spatial autocorrelation. Wang et al. (2020) used the process model and satellite data to calculate the process of change of NPP in China over the years. Yu (2020) analyzed the temporal and spatial variations of grassland NPP using the vegetation photosynthetic efficiency model. Moreover, NPP can be used as an indicator to evaluate the regional eco-environment system (Taelman et al., 2016); it can reflect the state of ecological changes (Williamson et al., 2012), such as crop yield (Jaafar and Ahmad, 2015; Hadian et al., 2019; Zhang et al., 2019), eco-environment sensitivity (Nayak et al., 2010; Xing et al., 2010), and surface carbon storage and accumulation (Thevs et al., 2013). Numerous studies have used vegetation productivity as an index in the assessment of land degradation and restoration (Fay, 2008; Wairiu, 2017; Kang et al., 2019). In addition, various external factors have been combined with NPP to analyze the influences of climate change (Nemani et al., 2003; Wang et al., 2020), human activities (Zhou et al., 2015; Wang et al., 2016), environmental variables (Zhang et al., 2019; Koju et al., 2020), and other factors on NPP as well as the response of NPP to these factors. Most previous studies focused on the temporal and spatial variation trends of NPP of the vegetation at the large or medium scale, whereas the changes of NPP of the vegetation and its interaction with restrictive factors at the small scale were often ignored.

The Qira Oasis is located in the Tarim Basin, China. Due to its distinct arid climatic conditions and geographical location, eco-environment of the Qira Oasis is extremely vulnerable. Protecting the eco-environment of the Qira Oasis plays a vital role in local sustainability. In arid regions, although NPP is a significant indicator reflecting the regional vegetation conditions, groundwater is also an important factor influencing the change of surface processes (Wu et al., 2010; Zhao et al., 2020). Groundwater impacts the meadow vegetation in the oasis transition zone and directly determines the economic development and vegetation growth in the oasis. In recent years, as the fluctuation of groundwater in the Qira Oasis has been relatively large, its impact on oasis vegetation has become increasingly evident (Ding et al., 2003). Therefore, the aims of this study are to: (1) adopt the CASA model modified by Feng et al. (2014) to simulate the temporal and spatial variation characteristics of NPP of the vegetation in the Qira Oasis during the period from

2006 to 2019; and (2) analyze the relationship between NPP of the vegetation and groundwater in the oasis based on the inversion of the high-precision Normalized Difference Vegetation Index (NDVI) data. To achieve these goals, we carried out the following three aspects of research: (1) calculating vegetation NDVI of the Qira Oasis based on the remote sensing data in June of 2006–2019; (2) analyzing the temporal and spatial variations of NPP of the vegetation using the modified CASA model; and (3) identifying the relationship between vegetation and groundwater depth in the oasis.

2 Materials and methods

2.1 Study area

The Qira Oasis, with the geographical coordinates of 35°18′–39°18′N and 80°03′–82°10′E, is located on the south margin of the Taklimakan Desert in the Tarim Basin of China. The terrain of the Qira Oasis is high in the south and low in the north, with an elevation between 1296.5 and 1370.5 m; the middle part of the oasis has developed into an inclined piedmont plain. Farmland occupies a significant proportion of the oasis, followed by grassland and forest (Fig. 1). The oasis is characterized by an arid desert climate, with an annual average temperature of 11.9°C, an extreme maximum temperature of 42.0°C, and an extreme minimum temperature of 23.9°C. The mean annual precipitation is only 35.1 mm, while the evaporation is close to 2595.3 mm. The annual frost-free season is about 230 d, and the annual total sunshine duration is over 2868 h. The mean annual runoff of the Qira River flowing through the oasis is 1.28×10^8 m^3.

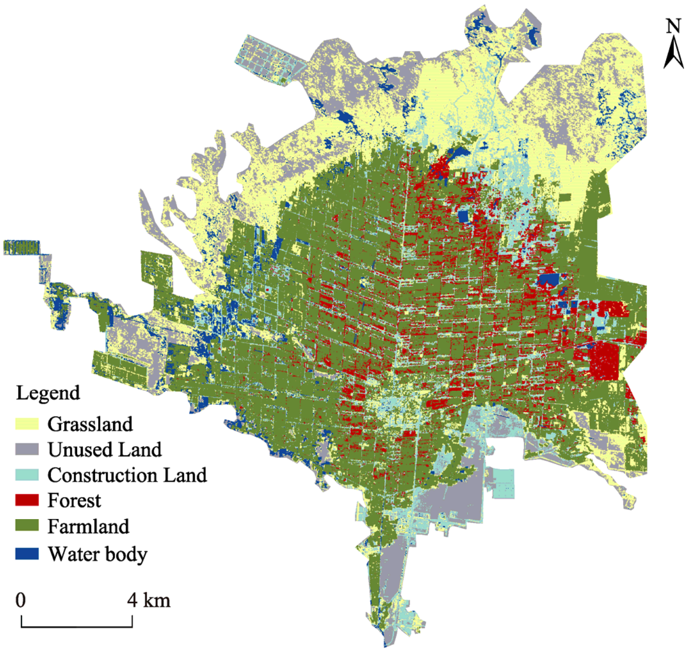

Fig. 1 Land use classification of the Qira Oasis

2.2 Research data and sources

The meteorological data used in this research, which included daily temperature, precipitation, evaporation, humidity, and solar radiation from 2006 to 2019, were obtained from a ground meteorological station in the Qira Oasis. The groundwater data were measured from 23 monitoring wells in the Qira Oasis in June of 2008–2015. As it is difficult to obtain the groundwater data, this study lacks data of 2012 and 2013. These groundwater data were from the Qira National Station of Observation and Research for the Desert-Grassland Ecosystem, China.

The land use data were accessed on 11 December 2020 from the Cloud Platform for Resource

and Environment Data of the Chinese Academy of Sciences (http://www.resdc.cn/). The land use types were divided into six categories: forest, grassland, farmland, water body, construction land, and unused land (Fig. 1), in which the grassland was further classified into three sub-categories, including low-coverage grassland, medium-coverage grassland, and high-coverage grassland. Low-coverage grassland refers to natural grassland with coverage of 5%–20%. This type of grassland is sparse and highly short of water, and the utilization condition is poor. Medium-coverage grassland refers to natural grassland and improved grassland with coverage of 20%–50%. High-coverage grassland refers to natural grassland, improved grassland, and mowed grassland with coverage of more than 50%, which usually has an adequate moisture conditions and thick grass cover. The land use types were interpreted, classified, and digitalized in accordance with the land classification system of the Chinese Academy of Sciences, and the interpretation results were verified with field investigation.

The remote sensing data were 14 Landsat 5 and Landsat 7 images from 2006 to 2019 accessed on 5 December 2020 from the United States Geological Survey (https://earthexplorer.usgs.gov/), with a spatial resolution of 30 m. The cloud content was less than 10%. ENVI software was used to conduct pre-processing such as radiometric calibration, atmospheric correction, and cutting on the remote sensing data before calculating the vegetation NDVI. We estimated the NPP of the vegetation based on the NDVI using the CASA model.

2.3 Methods

2.3.1 Calculation of the NDVI

The formula for the calculation of the NDVI is as follows:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{R}) / (\mathrm{NIR} + \mathrm{R}), \tag{1}$$

where R refers to the red band of visible light; and NIR refers to the near-infrared band. Among them, the red band of the TM sensor is Band 3, the near-infrared band is Band 4, the red band of the ETM+ sensor is Band 4, and the near-infrared band is Band 5. The calculation result shows the single-band image expressed in gray level whose pixel range is from –1 to 1 generally.

2.3.2 Calculation of vegetation NPP

The CASA model has been widely applied among currently available models for remote sensing estimation of NPP of the vegetation. In addition to the impact of characteristics of the living habitat on vegetation, it also includes characteristics of the internal action mechanism of the vegetation. The model is mainly determined by the photosynthetically active radiation and the solar energy utilization efficiency of the vegetation (Piao et al., 2001):

$$\mathrm{NPP} = \mathrm{APAR} \times \varepsilon, \tag{2}$$

where NPP refers to the net primary productivity of the vegetation (g C/m^2); APAR refers to the solar radiation absorbed by the vegetation (MJ/m^2); and ε refers to the solar energy utilization efficiency of the vegetation (g C/MJ).

The restrictive factor APAR can be calculated as follows:

$$\mathrm{APAR} = \mathrm{SOL} \times \mathrm{FPAR} \times 0.5, \tag{3}$$

where SOL refers to the total solar radiation (MJ/m^2), which was taken from the measured data of local meteorological stations; FPAR refers to the proportion of photosynthetically active radiation absorbed by the vegetation, which is determined by the maximum and minimum NDVI values and the maximum and minimum solar radiation of different vegetation types.

The solar energy utilization efficiency refers to vegetation's capacity to convert solar radiation into organics, which is related to the actual vegetation type, temperature, precipitation, and other environmental conditions. Its calculation formula is:

$$\varepsilon = T_{\varepsilon 1} \times T_{\varepsilon 2} \times W_{\varepsilon} \times \varepsilon_{\max}, \tag{4}$$

where $T_{\varepsilon1}$ and $T_{\varepsilon2}$ refer to the restrictive effect of temperature; W_{ε} refers to the restrictive effect of moisture; ε_{max} refers to the maximum solar energy utilization efficiency corresponding to different vegetation types (g C/MJ). The ε_{max} value was from the maximum solar energy utilization efficiency table proposed by Fang et al. (2003) by taking into consideration of the characteristics of arid

regions. In addition, the unit of temperature is Celsius (°C).

2.3.3 Slope trend analysis

One-dimensional linear trend analysis was adopted to carry out the research on the trend and magnitude of the temporal and spatial variations of NPP during the years from 2006 to 2019. The fitting of NPP variation trend was conducted at a pixel scale. The temporal variation characteristics and the regional spatial variation of each pixel were summarized to show the long-term temporal and spatial trend patterns of NPP in the region. Since the one-dimensional linear trend analysis can eliminate the impact of accidental abnormal factors on vegetation growth during the study period, it can reflect the NPP variation trend of the vegetation over a long time series more reliably. The calculation formula is as follows (Wang et al., 2020):

$$\theta_{\mathrm{slope}}=\frac{n\times\sum_{i=1}^{n}i\times \mathrm{NPP}_i-\sum_{i=1}^{n}\sum_{n=1}^{n}\mathrm{NPP}_i}{n\times\sum_{i=1}^{n}i^2-\left(\sum_{i=1}^{n}i\right)^2}, \tag{5}$$

where θ_{slope} refers to the trend line slope of the pixel regression equation; n refers to the time duration of the research data (a); and NPP_i refers to the average NPP value in the i^{th} year. If $\theta_{\mathrm{slope}}>0$, it means that the variation of NPP during the study period shows an increasing trend; if $\theta_{\mathrm{slope}}<0$, it means that the variation of NPP during the study period shows a decreasing trend.

2.4 Data analysis

The calculation of the NDVI mainly relied on the NDVI function of the ENVI software. In addition, the NPP distribution of different land use types in the Qira Oasis was calculated with the ArcGIS spatial overlay tool. The variation in the depth of groundwater was calculated by the Kriging interpolation method. This method is a regression algorithm for spatial modeling and interpolation of random processes based on covariance functions, which can be achieved using ArcGIS software.

3 Results

3.1 Variations in NPP of the vegetation

3.1.1 Temporal and spatial distribution characteristics of NPP

The temporal and spatial distribution of NPP in June of 2006–2019 calculated with the CASA model is shown in Figure 2. At the temporal scale, the range of NPP of the vegetation in the oasis in different years fluctuated to some extent, with the maximum value occurring in 2007 and the minimum value in 2016. The results shown in Figure 2 revealed that the distribution characteristics of NPP of the vegetation were basically the same in each year. The spatial distribution of NPP of the vegetation was obtained by calculating the average value of NPP pixel-by-pixel during the study period.

The NPP distribution in the Qira Oasis had a relatively significant spatial heterogeneity and was closely related to the land use types in the oasis. The farmland and forest with relatively high vegetation coverage were distributed inside the Qira Oasis, while the grassland and unused land with relatively low vegetation coverage were distributed on the margin of the oasis. Therefore, at the spatial scale, NPP in the Qira Oasis has always been higher in the internal area than on the margin (i.e., decreasing from the center to the edge) and the distribution of the maximum NPP values was scattered.

3.1.2 Temporal and spatial variations of NPP

As shown in Figure 3, the temporal variation of NPP in the Qira Oasis generally showed a slightly increasing trend (average increase rate of 0.07 g C/(m^2·month)) during the whole study period. Specifically, the values of NPP fluctuated significantly in recent years, with the range between 29.80 and 50.07 g C/(m^2·month) and the average value of 38.87 g C/(m^2·month). The maximum value was up to 50.07 g C/(m^2·month) in 2006, while the minimum value was only 29.80 g

C/(m^2·month) in 2016.

The pixel-by-pixel variation trend of NPP in June of 2006–2019 calculated with the one-dimensional linear regression model is shown in Figure 4a. At the temporal scale, the

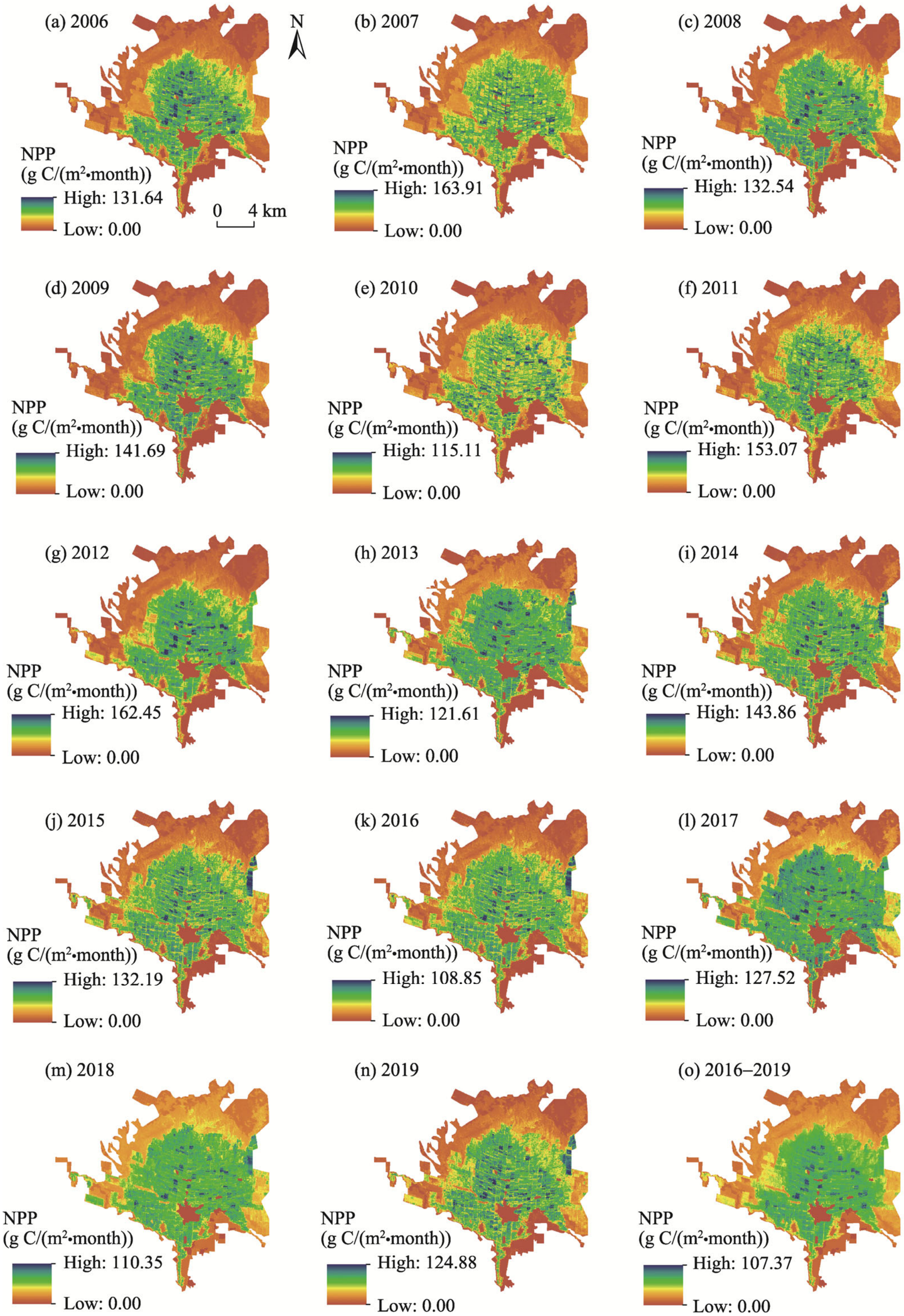

Fig. 2 Temporal and spatial distribution patterns of net primary productivity (NPP) in the Qira Oasis in June of 2006–2019 (a–o)

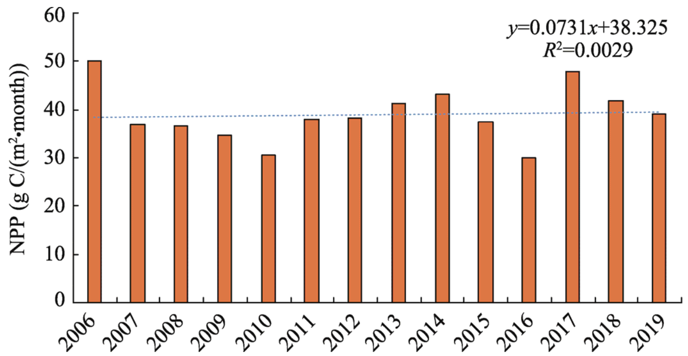

Fig. 3 Temporal variation of NPP in June of 2006–2019

variation characteristics of NPP varied in different spatial regions of the Qira Oasis. Based on the temporal variation of NPP, it was found that nearly 70% of the oasis area showed a positive variation of NPP, while 30% showed a negative variation of NPP. At the spatial scale, the relatively high temporal variation occurred on the eastern and western margins of the oasis (the increase rate mostly over 0.50 g C/(m^2·month)). The regions with negative variation were scattered inside the oasis, with the increase rate mostly between –0.50 and 0.00 g C/(m^2·month).

To further obtain the increasing and decreasing conditions of NPP in the Qira Oasis in the study period, we calculated the difference of NPP between June 2006 and June 2019, and produced the spatial distribution map of NPP difference in ArcGIS (Fig. 4b). The regions with decreasing NPP in the Qira Oasis were relatively large in the studied 14 years, with the total area of 163.21 km^2 (accounting for 64% of the oasis). These regions were mainly distributed on the margin of the oasis. The result indicated that compared with the initial year of the study (2006), the vegetation productivity in the Qira Oasis decreased and the vegetation was degraded.

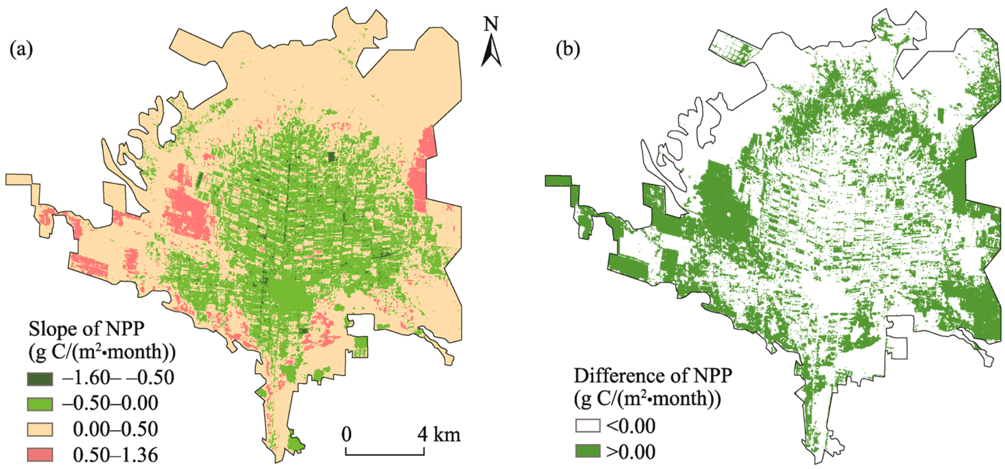

Fig. 4 Spatial distribution of trend slope of NPP in June of 2006–2019 (a) as well as spatial distribution of difference of NPP between June 2006 and June 2019 (b)

3.2 Distribution characteristics of NPP for different land use types

Figure 5 shows the average NPP values of four different land use types during the period 2006–2019; the deceasing order of NPP values are as follows: forest (82.95 g C/(m^2·month)), farmland (61.51 g C/(m^2·month)), grassland (58.39 g C/(m^2·month)), and unused land (10.37 g C/(m^2·month)). In addition, the land use types showing obvious NPP fluctuation during the study period were classified into two groups. Specifically, the NPP fluctuation of farmland and forest was basically identical, with the maximum value appearing in 2012 (76.96 and 115.13 g C/(m^2·month), respectively) and the minimum value in 2010 (44.92 and 62.16 g C/(m^2·month),

respectively). Eventually, the NPP variation of forest showed a decreasing trend, while the NPP variation of farmland showed a slightly increasing trend. The NPP fluctuation of grassland and unused land was basically the same, with the maximum value appearing in 2017 (92.53 and 15.20 g C/(m^2·month), respectively) and the minimum value in 2009 (40.35 and 5.53 g C/(m^2·month), respectively). The NPP fluctuation of both grassland and unused land showed an increasing trend during the research period.

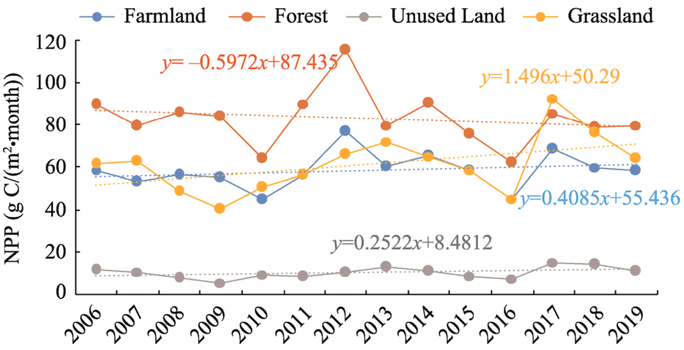

Fig. 5 NPP variation trend for different land use types in June of 2006–2019

3.3 Response of grassland to groundwater characteristics

3.3.1 Temporal and spatial distribution characteristics of groundwater in the oasis

Based on the groundwater data measured at 23 groundwater monitoring wells in the Qira Oasis in June of 2008–2015 (except for 2012 and 2013), we obtained the spatial distribution of groundwater depth using the Kriging interpolation method (Fig. 6). There was a significant spatial variability of groundwater depth in the Qira Oasis during these years. The depth of groundwater was deep in the south of the oasis and shallow in the north, showing a gradual increasing trend from south to north, which was basically consistent with the topography distribution of the oasis. After the unified classification of groundwater depth in these regions, we found that within the same range of groundwater depth, oasis area changed greatly over the years.

3.3.2 Relationship of grassland NPP and groundwater depth

The variation in the NPP of the vegetation can reflect the capacity of the ecosystem in a region. There are many factors influencing the variation of NPP of the vegetation. Water is the most important restrictive factor in arid oasis regions. However, the Qira Oasis has little precipitation and the surface water is mainly used for agricultural irrigation, so plant growth almost exclusively depends on groundwater. As shown in Table 1, for the grassland in the Qira Oasis, groundwater depth from deep to shallow was in the order of low-coverage grassland>medium-coverage grassland>high-coverage grassland, and NPP from high to low was in the order of high-coverage grassland>medium-coverage grassland>low-coverage grassland. With the increase in groundwater depth, vegetation coverage declined and NPP of the vegetation also decreased. Among them, groundwater depth in low-coverage grassland exceeded 10.0 m, which is extremely unfavorable for the growth of plants.

To further analyze the response of grassland to groundwater depth in the Qira Oasis, we selected plants including sacsaoul, rose willow, reed, and grasses to analyze the variations of NPP during the groundwater observation period, as well as to explore the correlation between NPP of the vegetation and groundwater depth. As shown in Figure 7, among the four types of vegetation, NPP value of reed was the highest from 2008 to 2015 (except for 2012 and 2013), with an average value of 47.97 g C/(m^2·month) (ranging from 38.17 to 58.94 g C/(m^2·month)). NPP value of grasses ranked the second, with an average value of 33.51 g C/(m^2·month) (ranging from 26.68 to 40.72 g C/(m^2·month)), followed by rose willow, with an average value of 21.55 g C/(m^2·month) (ranging from 14.97 to 29.68 g C/(m^2·month)). NPP value of sacsaoul was the smallest, with an average value of 25.95 g C/(m^2·month) and ranging from 16.22 to 39.04 g C/(m^2·month).

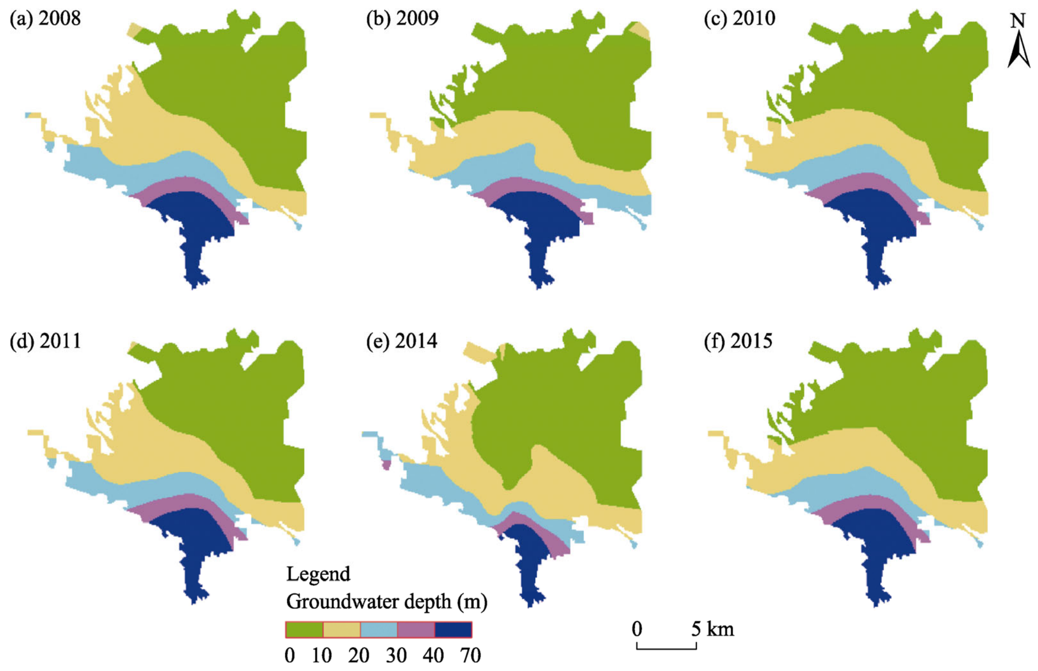

Fig. 6 Spatial distribution of groundwater depth in the Qira Oasis in June of 2008 (a), 2009 (b), 2010 (c), 2011 (d), 2014 (e), and 2015 (f)

Table 1 Net primary productivity (NPP) and groundwater depth (GWP) of grassland with different coverages in the Qira Oasis in June of 2008–2015 (with exceptions of 2012 and 2013)

Grassland type	2008		2009		2010	
	NPP (g C/(m²·month))	GWD (m)	NPP (g C/(m²·month))	GWD (m)	NPP (g C/(m²·month))	GWD (m)
High-coverage grassland	19.99	7.38	17.52	6.62	19.00	5.46
Medium-coverage grassland	15.31	8.93	12.43	7.47	16.25	6.73
Low-coverage grassland	13.46	12.61	10.39	14.84	15.30	11.82

Grassland type	2011		2014		2015	
	NPP (g C/(m²·month))	GWD (m)	NPP (g C/(m²·month))	GWD (m)	NPP (g C/(m²·month))	GWD (m)
High-coverage grassland	23.77	7.67	25.85	9.76	23.45	6.42
Medium-coverage grassland	17.50	8.82	21.05	10.83	18.42	7.81
Low-coverage grassland	15.35	12.74	18.31	15.11	16.90	12.23

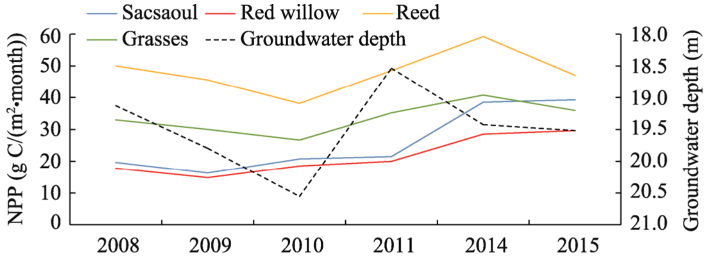

Fig. 7 Variations of NPP of the four different vegetation types and groundwater depth in June of 2008–2015

During the study period, it was found that reed contributed the most to the productivity of the vegetation in the Qira Oasis. As demonstrated in Figure 7, there was a negative correlation between NPP of all four vegetation types and groundwater depth, indicating that NPP of the vegetation declined with the decrease of groundwater depth. The correlation coefficients between

NPP of the vegetation and groundwater depth were –0.29 (sacsaoul), –0.35 (red willow), –0.89 (reed), and –0.98 (grasses), which indicated a stronger negative correlation of groundwater depth with NPP of reed and grasses.

4 Discussion

4.1 Degradation of the Qira Oasis and decline of vegetation productivity

In arid regions, surrounded by deserts, oasis has a certain scale of biological community, which can form relatively stable heterogeneous ecological landscape, exhibit obvious microclimate effects, and play a vital role in the development of arid lands (Thomas et al., 2006; Yu et al., 2015). NPP of the vegetation in an oasis can reflect the productivity capacity of a plant community under natural environmental conditions. At the spatial scale, NPP was higher in the interior and lower on the margin of the Qira Oasis, decreasing from the center to the edge; at the temporal scale, NPP showed a slightly increasing trend during the whole study period. According to the results of temporal variation of NPP, we found that the regions with decreasing NPP on the margin of the Qira Oasis was increasing to 163.21 km^2, accounting for 64% of the oasis area, which indicated that vegetation productivity in the oasis had declined over the studied years. In the past few decades, due to the fast growth of population, the demand for water resources had sharply increased; in addition, the main industry of the Qira Oasis was agriculture and the agricultural irrigation region that relied heavily on water supplement has been continuously expanding (Zhang et al., 2019). However, the Qira Oasis is located in the Taklimakan Desert, one of the driest places in the world, where precipitation and surface runoff are inadequate (Yu et al., 2017; Bi et al., 2020). The lack of water resources is a possible reason for the decline of vegetation productivity in the Qira Oasis, leading to the degradation of the oasis.

4.2 Impact of regional land use change on NPP variation

Land use change directly influences the type, structure, and function of an ecosystem, thus affecting vegetation productivity (Liu and Gao, 2009). In the Qira Oasis, the variation of vegetation NPP for different land use types exhibited different characteristics. Specifically, NPP of farmland and grassland showed an increasing trend, with the increase rate of grassland faster than that of farmland. NPP of forest showed a decreasing trend, with the peak value appearing in 2012. Overall, the fluctuation in NPP of forest, farmland, and grassland was relatively large, which indicated that these three land use types showed poor stability and large variation during the study period. Some of the possible reasons for such fluctuation are climate change and human activities such as agricultural encroachment and illegal logging. Agricultural encroachment has been a serious problem in the whole oasis for a long time. Most people in this oasis are occupied in agriculturally-related work, but the amount of land suitable for farming is limited. This has led to the encroachment of some natural forest and grassland (Sun et al., 2021). Climate change and the shortage of water resources are also the possible causes of changes in land use types, exerting negative effects on NPP.

4.3 Response of grassland NPP to groundwater depth

Owing to the extreme arid climate conditions and scarce precipitation in the Qira Oasis, precipitation has little effect on plant growth. Most of the water needed for the growth of vegetation mainly comes from groundwater, so groundwater is a key factor restricting the growth of vegetation in the oasis. Variation in the depth of groundwater can determine the direction of vegetation succession in the Qira Oasis. The existing studies have showed that the vegetation distribution pattern in the transitional zone on the margin of the Qira Oasis has certain regularity with the variation of groundwater depth (Helge et al., 2003; Qian et al., 2018; Zhao et al., 2020), which suggested that groundwater depth can have a significant impact on the oasis vegetation.

For this study, we found that with the recovery of groundwater level in the Qira Oasis during the period 2008–2015, NPP values of all types of vegetation with different coverages increased, which indicated that groundwater depth affected the vegetation productivity in the oasis. The

deeper the groundwater depth, the smaller the NPP; and NPP is more sensitive to groundwater depth. These findings are consistent with the research results of Zhang (2001) and Mao et al. (2012), indicating the applicability of this research.

In 2014, the oasis area with groundwater depth between 40.0 and 70.0 m decreased significantly, indicating that groundwater depth increased in 2014 to some extent. Groundwater, as one of the key factors in the surface change and evolution of the oasis in the arid regions, determines the succession direction of the vegetation in the oasis. The variation of groundwater depth in the Qira Oasis was relatively large, which had a significant impact on the survival and growth of the oasis vegetation that relied on groundwater.

5 Conclusions

In this study, we conducted a comprehensive analysis on the temporal and spatial variations of NPP in the Qira Oasis from 2006 to 2019 based on the modified CASA model. NPP was higher in the interior and lower on the margin of the oasis, decreasing from the center to the edge. NPP of the vegetation ranged from 29.80 to 50.07 g C/(m^2•month) during the study period, with the maximum value appearing in 2006 and the minimum value in 2016. The regions with the decreasing NPP accounted for 64% of the oasis area, which suggested that vegetation productivity in the oasis declined over the years. For different land use types, NPP of forest showed a decreasing trend, while that of farmland and forest increased. Groundwater depth was the main factor affecting the vegetation characteristics in the oasis.

This study provides a new idea for the research of oasis vegetation productivity, and also complements the previous studies on the relationship between groundwater level and vegetation growth in the Qira Oasis. For future study, it is necessary to analyze the influencing factors of NPP change in the Qira Oasis and quantify the influence degree of each factor, so as to provide information for local environmental restoration.

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